

## Perspective

# Algorithmic aesthetics: Cognitive perspectives on AI-generated visual art

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## SUMMARY

In recent years, the use of generative artificial intelligence has proliferated across various domains, ranging from advertising and social media to the generation of visual artwork for presentation at esteemed art exhibitions and for sale on the art auction market. Despite its growing prevalence, empirical data show that people maintain a clear bias against AI-generated visual art when they are aware of its artificial origins. Here, we explore *why* this bias might exist and whether its existence dooms the eventual acceptance and even celebration of art generated by artificial means. We do this by bringing together recent empirical evidence from the disciplines of neuroaesthetics, social cognition, art history, and human-machine interaction to develop several new perspectives that are ripe for empirical evaluation. Given the growing momentum and outlook of AI-generated art, particularly image generation, in today's society, our aim with this paper is to provide novel evidence-based propositions for understanding the relationship between visual art and artificial intelligence with a clear focus on social cognitive neuroscience perspectives.

## BRIEF INTRODUCTION TO AESTHETIC EXPERIENCE OF AI-GENERATED ART

### The media perspective: Insights from art historians, AI tool creators, the art market, and artists

Recent advances in AI tools for art generation have sparked passionate debates and deep discussions across a growing number of public domains. To date, AI terminology reflects a range of nuances and interpretations, largely shaped by the type of AI tools used and the degree of human involvement in the creative process. Across this paper, we adopt the general term **AI-generated art** to capture the broad-ranging discussions concerning biases against the use of AI in artistic creation and evaluation. These discussions have involved art historians questioning the role of AI in assessing the artistic value of artworks and AI developers defending their innovations. Similarly, the art market has advocated for the new economic opportunities these tools create, while both the general public and artists express a mixture of praise and concern regarding the impact of AI on artistic creativity.<sup>1,2</sup> For example, Drimmer, an art historian,<sup>1</sup> has argued that AI-generated art fails to promote knowledge growth or the development of new ideas, as it does not provide insights into the functions of art, the intentions of artists, or their creative processes. Instead, the increasing media attention on AI art tools is seen as fostering soft diplomacy for AI, rather than advancing art history research. Drimmer also argues that framing AI as a tool for art understanding primarily benefits scientific fields at the expense of the humanities, because it raises awareness and attracts funding for AI-related scientific research but

risks reducing art to merely a “toy in the sandbox of scientists.”<sup>1</sup> Criticisms also extend to the ethical implications of generative AI, with Goetze<sup>3</sup> arguing that such systems appropriate artists’ creative work without consent or compensation. This constitutes “labor theft” and reframes debates on AI art in terms of exploitation that requires redress, rather than technological novelty and innovation to be celebrated.

In contrast, the creators of the Artificial Intelligence Creative Adversarial Network (AICAN), which has been designed to produce artificial art at Rutgers’ Art & AI Lab, have argued that AICAN was developed primarily for creative purposes. Mazzone and Elgammal<sup>4</sup> have described AICAN as more of an autonomous artist than a mere tool, highlighting its artistic role in generating original artwork. The AICAN tool started to receive public recognition in 2017 when its art was showcased at venues across Frankfurt, Los Angeles, and New York. Across these events, the authors have noted viewers’ overwhelming positive appreciation responses to AI-generated art, with many people expressing disbelief that the featured artworks were generated by an AI algorithm rather than created by human artists. Furthermore, the AICAN tool has been featured across various media platforms, including daily newspapers (e.g., Boston Globe) and TV networks (e.g., CBS or HBO). These media portrayals have framed AICAN as an intrinsically creative process, rather than a technological output intended for artistic acclaim in high-profile galleries or for financial gain at prominent art auction houses.<sup>4</sup>

From the art market’s perspective, AI-generated art has been recognized for its potential to create new business opportunities.



In 2018, the art auction market reported the first milestone, when the *Portrait of Edmond Belamy*, an artwork produced by a generative adversarial network (GAN), was auctioned at Christie's for \$432,500.<sup>5</sup> When discussing its own financial success in auctioning this piece, Christie's highlighted the artwork's non-human origins and the creative role of the algorithm.<sup>2</sup> Media coverage, such as Reuters<sup>6</sup> and NDTV<sup>7</sup> collectively celebrated this event as a new era in art, marking its debut on the global art auction stage and highlighting changing perceptions of art's role and value. While the art market has referred to generative AI art as a milestone in artistic and commercial possibilities, a review by Jiang et al.<sup>8</sup> has highlighted clear harms reported by professional artists, with economic loss playing a central role alongside reputational damage, plagiarism, copyright risks, and moral fairness. This suggests that art market's enthusiasm is counterbalanced by artists' realistic and well-documented reasons of resistance.

However, the general public has greeted AI-generated art with much more ambivalence. For example, a photography project by Mike Tyka titled "*Portraits of Imaginary People*" used GANs and **Deep Dream** and has received artistic acclaim at prominent venues, such as ARS Electronica, Christie's, and the New Museum in Karuizawa, Japan.<sup>9</sup> However, when Jason M. Allen won a digital art prize with assistance from the **MidJourney** AI tool in 2022, it led to accusations of cheating. Critics argued that the use of AI in creating his winning piece undermined the value of human creativity, which, in the future, may put the artistic profession itself at risk.<sup>10</sup> These examples illustrate some of the prevailing tensions and debates surrounding what role AI could or should play in creative processes. While some welcome the creative potential of AI, others express concern about the loss of human artistry and the potential displacement of human artists.<sup>1,4,10,11</sup>

### Research findings on the AI-generated art and aesthetic experience

In the domain of empirical research, studies exploring people's perceptions of AI-generated art have uncovered mixed patterns of results. Investigations into art novices' ability to distinguish between human-made art and AI-generated art have consistently demonstrated low accuracy rates in AI art detection.<sup>12–17</sup> For example, a study by Gangadharbatla<sup>15</sup> investigated people's ability to accurately differentiate human-made art from AI-generated art. The stimuli used were AI-generated and human-made artworks, including representational and abstract forms, all of which were taken from the internet. The results indicated that people, in general, were unable to accurately identify AI-generated art and furthermore were more likely to associate representational art with human-made art and abstract art with AI generated. The authors interpreted this pattern of findings to mean that, in addition to the low accuracy of AI art detection, people's confusion may also stem from the nature of the content depicted in the artworks. Specifically, the level of abstraction could be a contributing factor to this detection challenge.

Furthermore, the aesthetic valuation of AI-generated art appears to be modulated by pre-existing biases regarding the creative skills of AI. A recent study by Agudo et al.<sup>18</sup> demonstrated that awareness of a musical piece as AI-generated led to reduced perceptions of its emotional depth and overall artistic

quality. Similarly, findings by Hong et al.<sup>19</sup> indicated that people who were open-minded and receptive to the idea of AI as a creative entity were more likely to positively evaluate AI-composed music in terms of aesthetic appeal and craftsmanship. The idea that attitudes toward AI matter is further supported by recent work by Darda et al.<sup>13</sup> The researchers found that, in instances where participants showed more favorable attitudes toward the overall utility of AI, they also assigned higher values to both AI-generated and human-produced texts. This suggests an association between positive attitudes toward AI and an increased acceptance of AI applications. These findings collectively suggest that preconceived notions and biases regarding AI's artistic abilities impact the overall assessment of AI-generated art.

Moreover, across various artistic domains (e.g., visual art, dance, and music), research has demonstrated a clear aesthetic bias against AI-generated art when people are aware of an artwork's AI origins.<sup>12–14,19–22</sup> For example, Ragot et al.<sup>23</sup> tested a large sample size ( $N > 565$ ) to compare human-made art and AI-generated art across various aesthetic dimensions. The results showed that human-made artworks were rated higher on different dimensions of liking, beauty, and novelty than AI-generated art, suggesting a clear aesthetic preference for human art. Furthermore, recent work from our team attempted to tap into people's judgments about morality and AI-generated art by combining explicit and implicit paradigms.<sup>24</sup> Across three pre-registered experiments, our results yielded important insights into the moral and aesthetic dimensions of AI-generated art. Specifically, we found that: (1) providing factual information about AI systems consistently diminished both moral acceptability and aesthetic evaluations of AI art, (2) moral acceptability of AI-generated art remains largely unaffected by different information doses about its success beyond the factual information about AI systems, and (3) implicit associations between human art and AI-generated art and their perceived attributes were similar. Our findings highlight the essential role that information about AI systems plays in shaping both moral evaluations and esthetic perceptions.

Overall, the body of research reviewed earlier suggests that, while people often find it challenging to distinguish between AI-generated and human-made art, knowledge about an artwork's artificial origin tends to diminish perceptions of its craftsmanship, emotional value, and aesthetic appreciation. This could be linked to the idea that AI-generated art lacks the human-like artistic and creative qualities necessary for building a meaningful and emotional connection between the viewer and the artwork. This perception is likely to contribute to the development of a general negative bias against AI-generated art. It is also important to highlight that these studies reflect public perceptions as they stand today. Given the rapidly evolving nature of AI generative tools in producing art, these perceptions are subject to continue to develop and change.

### UNDERSTANDING THE BIAS AGAINST AI-GENERATED ART—THEORETICAL AND EMPIRICAL INSIGHTS

#### What is art?

To identify the possible factors contributing to the current bias against AI-generated art, it is essential to first explore how the

concept of art has been historically conceptualized. Defining art is inherently complex and multifaceted. Acknowledging this, and to provide a clear and structured foundation for our discussion, we adopt working definitions grounded in intentionalism, formalism, and the expressive view of art. Throughout centuries, art has been defined as a uniquely human activity, created with intentional expression and creativity, using cultural and historical conventions, and conveying original ideas, emotions, and experiences.<sup>25–32</sup> According to this intentionalist view, art is a form of communication in which the artist deliberately seeks to convey specific ideas or emotions, intentionally aiming for a meaningful connection with the audience.<sup>25,30</sup> Furthermore, artistic expression is typically shaped by cultural and historical traditions, including techniques, styles, and media of presentation, thus reflecting the cultural and historical context, norms, and values of its time.<sup>28,33</sup> More broadly, art is often seen as an expression of creativity and skill, to convey original ideas and emotions.<sup>29</sup> In comparison, AI-generated art might be perceived as diverging from traditional artistic definitions, unless one considers that AI generative models are trained on extensive collections of human-made art. Therefore, it could be argued that conventional art definitions may serve as a barrier to broader public acceptance of AI-generated art.

Lewis Hyde's *The Gift*,<sup>34</sup> influential for over four decades, examines how artists' work is valued and monetized in our commercial society and provides a valuable lens for evaluating deeper assumptions about artistic value that underpin resistance to AI art. Hyde's central distinction between gift and market economies directly addresses how we conceptualize artistic creation and worth. The intentionalist view of art introduced earlier implicitly assumes that art emerges from a gift relationship: the artist's creative labor represents a form of giving that creates social bonds and meaning between creator and audience. AI-generated art fundamentally challenges this framework by potentially commodifying the creative process itself, raising critical questions about whether art can maintain its transformative social function when produced algorithmically. Hyde also conceptualizes the artist as a conduit through which cultural gifts flow rather than as their originating source, suggesting that, if human artists have always transmitted inherited cultural knowledge, AI might represent a new form of this transmission rather than a complete departure from artistic tradition. Finally, Hyde argues that gifts must be transformed and passed forward to maintain their vitality, prompting the question of whether algorithmic recombination constitutes the kind of meaningful transformation essential to art's gift economy. Hyde's framework thus reveals how debates about AI-generated art extend beyond definitional concerns to fundamental questions about the social and economic foundations of artistic practice.

Returning to empirical research, we can find further ideas about what might underpin the negative bias many people hold against AI-generated art. Some researchers suggest that the anti-AI bias may stem from concerns that AI could outperform and displace human artists by producing art more rapidly and with greater quality.<sup>21,35,36</sup> For example, in Western art, painting has long been celebrated as one of the highest forms of human artistic expression, valued for its intricate interplay of visuospa-

tial abilities, motor skills, cognitive reasoning, and creative abilities, all of which require a sophisticated level of expertise acquired through lengthy and repeated practice.<sup>37,38</sup> In contrast, the idea that AI algorithms have the potential to create art more rapidly and with quality that rivals or surpasses human efforts may contribute to the negative perceptions surrounding AI-generated art.

Furthermore, some have argued that AI-generated art poses a fundamental challenge to our entrenched beliefs in human exceptionalism, questioning the assumed superiority of human creativity over that of machines.<sup>39–42</sup> Consequently, it could be argued that people tend to downplay the artistic value of AI-generated art as a means of protecting their threatened anthropocentric perspective. Providing support for the human exceptionalism idea, Millet et al.<sup>40</sup> found that artworks were less preferred when identified as AI-generated rather than humanmade, primarily due to perceptions of diminished AI creativity and its reduced capacity for emotional engagement. Interestingly, this bias was more pronounced among people with stronger anthropocentric beliefs about creativity. This suggests that the aesthetic bias against AI-generated art is influenced by an anthropocentric view that constrains creativity in humans.

Moreover, many art historians, artists, and educators have argued that the arts inherently involve physical engagement with our bodies—this is evident in the performing arts, such as dance, music, mime and theater, as well as in visual arts, such as painting and sculpture. Dewey,<sup>43</sup> for example, emphasized the importance of artists' hands and tactile involvement in the artistic process within the visual arts, arguing that art is fundamentally a bodily experience. Climenhaga<sup>44</sup> extended this idea when discussing Pina Bausch's dance choreography, where the body acts as a medium for storytelling and emotional expression. From an educational perspective, Lu<sup>45</sup> has conducted interviews with art teachers to explore the perceptual differences between human-made and AI-generated art. This research revealed that art teachers often perceived AI-generated art as lacking emotional depth, attributing this to the absence of tactile (or bodily) engagement, which they saw as essential to traditional painting and artistic skills. Given the long-standing understanding of art as an embodied practice, the absence of immersive, embodied, and tactile experiences in AI-generated art may further contribute to the enduring negative biases people express against it.

### Dual perspectives on the imitation theory

To understand the factors contributing to the existing bias against AI-generated art, we propose two theoretically and empirically supported concepts—imitation in art and imitation in social cognitive neuroscience—as foundational frameworks for this analysis. From the arts perspective, it has been argued that the value of art is often assessed based on a balanced level of imitation of reality, with the highest-quality artworks achieving neither more nor less imitation of real life. In social cognitive neuroscience, imitation has been recognized as a fundamental mechanism through which people learn complex skills, socially engage with others, and establish affiliative bonds within groups. These insights together provide a valuable basis for understanding the persistence of the bias against AI-generated art today.

### Art and aesthetics

The imitation theory represents one of the most prominent theoretical frameworks for explaining art creation and art appreciation. While Aristotle provides us with one of the earliest formal discussions of imitation (or “mimesis”) in his book *Poetics*, which dates from the 4<sup>th</sup> century BCE,<sup>46</sup> the conceptual meaning of imitation has changed over the centuries.<sup>47,48</sup> In Antiquity, imitation was primarily understood as copying nature, whereas the Renaissance expanded upon this notion, providing more elaboration on the idea of imitation. During that time, imitation was conceptualized as being faithful to nature, especially on the ideal aspects, such as the perfect physical beauty rather than the mundane and imperfect aspects of real life.<sup>47,49</sup> In the 19th century, however, artistic movements such as Impressionism started to further diverge from the original theory by emphasizing the depiction of reality as perceived by the viewer.<sup>47,50</sup> This shift in framing the concept of imitation culminated in the avant-garde movement, where art increasingly expressed concepts rather than direct representations or imitation of physical reality.<sup>51,52</sup> In modern times, the theory has embraced a pluralistic perspective, acknowledging that artworks not only imitate reality but also convey the artist’s ideas, emotions, and experiences.

Traditionally, the assessment of artistic skill, art status, and aesthetic value of artworks has been closely linked to the conceptual framework of imitation. That means that the degree to which an artwork succeeds in faithfully representing visual reality or an established realistic art style had served as a benchmark in evaluating its artistic quality and aesthetic worth.<sup>48</sup> For example, Leonardo da Vinci believed that the value of a painting was directly proportional to its fidelity in depicting its subject, while Gustave Courbet, centuries later, argued that painting could only achieve its purpose by faithfully representing reality.<sup>53,54</sup> Moreover, depicting reality with fidelity was also fundamental to artists’ public acclaim. Their artworks were celebrated for achieving the right balance in capturing reality—neither less imitation, nor more—thereby meeting the standards of artistic excellence historically valued (see Figure 1, human-made art, Figures 1D and 1E examples).

However, with Post-Impressionism, artists such as Paul Cézanne marked an important departure from realistic imitation of reality. Cézanne rejected the notion that painting should replicate nature, instead focusing on the construction of visual form.<sup>55</sup> Cézanne famously stated he “renders nature through the cylinder, sphere, and cone,” emphasizing his focus to portray the inherent geometrical structures of nature rather than imitating its appearance. This novel approach led initially to severe criticism from contemporary art critics, who labeled Cézanne an “amateur” lacking artistic skill, and respect to artistic tradition.<sup>56</sup> Over time, however, perceptions changed, with Cézanne eventually being celebrated by the Fauves and Cubists as “the father of us all”.<sup>56</sup> In the same vein, before Fauvism and Cubism gained acceptance as important movements in art history, they were initially met with criticism. Fauvism, with its non-naturalistic colors, simplified forms, and spontaneous brushstrokes, and Cubism, known for its fragmented and multi-perspective approach,

were viewed as radical deviations from established imitation artistic conventions<sup>57–59</sup> (see Figure 1, human-made art Figures 1A–1C examples). It could be argued that this critical reception was rooted in a deep-seated belief that less imitation of nature, or the physical world, was equated with a deficiency in artistic craftsmanship. It is possible to see parallels between this historical perspective and contemporary biases against AI-generated art, which often shows low fidelity or less imitation of human-made art, potentially leading to similar perceptions of diminished artistic value and artistic skill.

Furthermore, the pursuit of high fidelity in mimicking nature has also attracted criticism. For example, the Photorealism and Hyper-Realism movements have faced scrutiny for imitating the reality to such an extreme level that they are perceived as lacking authentic creative vision<sup>60,61</sup> (see Figure 1, human-made art Figures 1F–1H examples). Contemporary photorealism artists such as Richard Estes and Chuck Close aimed to reproduce photographs with exceptional exactitude in their paintings, using a highly technical and machine-like precision. This emphasis on imitating reality as close as possible has been criticized for diminishing the artist’s personal interpretation and emotional input, as well as for prioritizing technical skill over artistic vision. For example, by focusing on rendering perceptions of the real world with as much mechanical accuracy as possible, such art often neglects the subjective and imaginative aspects that usually enrich artistic expression.<sup>60,61</sup>

While empirical research has yet to investigate whether the bias against AI-generated art may be explained by its level of imitation (e.g., less vs. more) compared to human-made art, historical parallels with human-made art might offer some valuable insights. For instance, when an AI algorithm fails to effectively imitate human art, that might be perceived as a lack of artistic skill (see Figure 1, AI-generated art - I, J, K examples; see figure legend for reasons why each example represents less imitation of human-created art). It could be argued that the current limitations of AI art algorithms, especially those based on GANs or LLMs with embedded image generators in faithfully imitating human-made art may arise from technical issues in how AI systems render artistic visual elements, such as color, lighting, the tactile qualities of the canvas (e.g., layering of brushstrokes) or the organization of compositional space. Moreover, the limited ability of AI art algorithms to imitate human art may be attributed to a superficial understanding of human culture, historical contexts, and artistic styles. This often leads to a less convincing narrative capacity when it comes to capturing and portraying historical figures, meaningful stories, or specific geographical locations. Furthermore, the typically reported emotional disconnection felt when viewing AI art compared to human-made art could indicate AI’s inability to evoke rich human-like emotions and meaningful experiences that resonate with viewers. On the other hand, more imitation of human art in AI-generated art might also be perceived as lacking authenticity, originality, and creative innovation, therefore failing to contribute meaningfully to the art world (see Figure 1, AI-generated art; Figures 1L–1N examples). More imitation could also be



## Imitation in Art

**Figure 1.** Shows a comparative analysis of imitation across the domains of art (human-made and AI-generated) to visualize how art value and art appreciation can be linked to different conceptions of imitation

The continuous line along the bottom represents a spectrum of imitation, ranging from less imitation on the left to more imitation on the right and distinguishes between human-made art (upper panel) and AI-generated art (bottom panel). The human-made artworks show examples of what was considered less imitation of the physical world at the time of their creation (A, *Guitar and Pipe* by Juan Gris, 1913; B, *Mont Sainte-Victoire* by Paul Cezanne, c.1895; C, *The Red Rocks* by Armand Guillaumin, 1984), balanced imitation (D, *Mona Lisa* by Leonardo da Vinci, c.1503-1519; E, *The Cliffs at Etretat* by Gustave Courbet, 1869), and more imitation (F = *Near Hunters Beach, Acadia National Park* by Richard Estes, 2008; G = *Woman Eating* by Duane Hanson, 1971; H = *Energy Apples* by Audrey Flack, 1980). The bottom panel shows AI-generated art examples taken from our recent work<sup>24</sup> using the AI image generation platform DALL-E 3 (OpenAI) and prompts inspired by Joaquín Sorolla's art. Here, the concept of imitation subsumes notions of reality as well as existing artistic styles. The initial outputs show less imitation of Sorolla's artistic style. Image I demonstrates less imitation primarily due to the implausibly large crowd depicted on a beach during fish sorting, a scene that sharply contrasts with Sorolla's historical depictions. In addition, the lack of spontaneity and emotional expressivity, combined with the standardized and stereotypical facial and bodily features, results in an overall mechanical impression. The landscape image (J) is exaggeratedly picturesque, with unnaturally vibrant colors that deviate entirely from Sorolla's Impressionist style. Furthermore, (K) presents an overly idealized portrayal of youthful beauty, happiness, and sentimentality. On the opposite side of the imitative spectrum for AI-generated art, we find AI iterations with far more imitation, closely mimicking Sorolla's style (L, M, and N). In these examples, the level of imitation is more pronounced, suggesting a possible impersonation of Sorolla's work, raising concerns about the distinction between inspiration and direct replication. The question mark in the middle part of the panel on AI-generated art suggests we do not yet have a firm conception of what balanced imitation might mean in the context of AI-generated art. This further suggests the potential for future AI-generated art to achieve an ideal balance of imitation and innovation. It also highlights the ongoing uncertainty regarding how this balance should be conceptualized and defined. Please note that, while our examples primarily focus on paintings and sculptures, the discussion could apply equally to other forms of visual art, including photography. The examples in Figure 1 are intended to illustrate a comparative analysis of imitation across human-made and AI-generated art and to depict positions along a less imitation—more imitation continuum rather than to empirically classify the degree of human or AI authorship.

Note. (A–E): images reproduced from the public domain. Source: WikiArt; (F–H): images reproduced under fair use for scholarly purposes. Source: WikiArt.

interpreted as deceitful, potentially undermining the uniqueness and importance of genuine human-created artworks. Overall, we suggest that AI-generated art has not yet achieved an optimal balance between imitation and innovation and also that a clear consensus still does not exist on what this optimal balance should entail. This reflects an important gap in understanding the sophisticated skillset that human artists have acquired and practiced through millennia. Highlighting the role of both imitation and innovation in human culture, Legare and Nielsen<sup>62</sup> argued that our species' remarkable cultural

achievements are not solely the result of imitation. Rather, it is the interplay between imitation and innovation that drives the finest cultural human accomplishments.

### Social cognitive neuroscience

The idea that less or more imitation of the world may be one important feature in the domain of art can be connected to the understanding of human social interactions. Indeed, imitation in the context of human social interactions—the copying of other people's behaviors—has been studied extensively in psychology, as well as social and cognitive neuroscience.<sup>63–66</sup> Imitative

behavior is underpinned by a widespread and distributed set of interacting cognitive and brain systems<sup>67</sup> and has been linked to a variety of key social functions, such as increased pro-social behavior and mutual liking.<sup>68–70</sup> Moreover, imitation has been argued to have been evolutionarily advantageous, as early humans likely relied on imitating gestures and behaviors to form social bonds and secure their inclusion in broader social groups.<sup>71,72</sup> Research on imitation has thus become central to our understanding of the cognitive and brain systems that orchestrate social life.

Rather than reviewing core features of imitation from the perspective of social and cognitive neuroscience in detail, what we focus on here are the parallels to the domain of art. Specifically, we focus on the idea that there could be a “sweet spot” of imitation, which is optimal in the sense that more or less imitation would be detrimental to social interactions. To start with, we quickly consider the extreme polar positions, which we feel are unlikely to facilitate social interactions. For instance, given what we know about the social benefits of imitation, a complete absence of imitation is likely to be suboptimal. Likewise, copying everything someone else does—movements, words, mannerisms—like a child’s game, would quickly become tiring, annoying, and socially awkward. But, if we go beyond these extremes, we can consider research that relates to two more subtle ways in which the amount of imitative behavior may or may not be used in an optimal manner: (1) in terms of responding to social contexts and (2) in terms of individual differences across the population. Figure 2 illustrates a comparative evaluation of imitation across social behaviors.

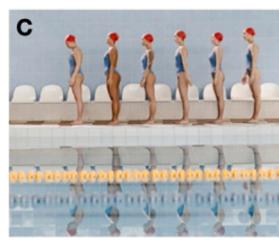
First, we consider more or less imitation, in terms of responding to social context. For example, research from developmental psychology has demonstrated that, in some situations, children show a strong tendency to **over-imitate**.<sup>64,73,74</sup> It has been proposed that children over-imitate to affiliate and emulate in-group members, as shown by their tendency to copy in-group rather than out-group members.<sup>74,75</sup> Adults also over-imitate, and it has been proposed to signal allegiance to a group, to foster a sense of unity and pro-social behavior.<sup>76</sup> Research has also shown that 5-year-old children display increased mimicry of facial expressions following the observation of third-party **ostracism**.<sup>77</sup> As such, it has been argued that ostracism represents an important contextual factor that might increase the tendency to mimic the behaviors of others to regain social inclusion.<sup>78</sup> Imitation also encourages empathic capacity toward other individuals,<sup>79,80</sup> suggesting that imitating others fosters greater understanding of others’ feelings, which in turn can strengthen interpersonal relationships and promote social cohesion. In summary, the ability to flexibly up-regulate imitative behavior in a manner dependent on the social context appears to be important for the building, maintaining, and restoring social relationships. Consequently, failure to up-regulate imitative behavior—that is, to provide less imitation, given the context—may weaken social bonds with our interaction partners.

A second way in which we can consider the impacts of less or more imitation is in terms of individual differences across the population. Various studies across different contexts and with different stimuli, populations (e.g., clinical vs. non-clinical), and

age groups consistently report that individuals with autism show a diminished ability for imitating social gestures and postures, such as blowing a kiss or waving goodbye compared to neurotypical individuals.<sup>81–83</sup> Given the social functions that appear to be served by imitation, reductions in imitative abilities among individuals may have important implications for social interpersonal connectedness, potentially hindering their ability to effectively engage in and interpret social interactions. As before, it also seems likely that more imitation, such as instances of **Echolalia or echopraxia**, could also be detrimental to social exchanges. While it is common to consider such variation in imitative abilities in relation to individuals that have received a clinical diagnosis, such as individuals with autism,<sup>67,84</sup> there are important reasons to avoid these categorical approaches.<sup>85,86</sup> A more general way to consider variation in imitation behavior would be as a general ability that could vary across the entire population, like other social skills and behaviors. As such, we might anticipate that some people are better than others at imitating “the optimal way” and thereby receiving the resultant social benefits.

Just as imitation theory in art suggests that artistic standards have traditionally relied on fairly accurately rendering reality rather than actively warping it, in social contexts, imitating others in a mostly naturalistic manner may appear crucial for effective social functioning. While there are substantial differences between the fields of arts and human neuroscience, both recognize the importance of imitating behaviors in shaping creativity, learning, and understanding of the social world. Finally, a few more parallels can be drawn between a balanced level of imitation in AI art and in human art and how this might influence how AI art is evaluated and accepted in human society. Humans learn through imitation, with generative learning theories suggesting that knowledge evolves through iteration and adaptation. Artmaking also involves iterative processes similar to those called upon during social and cognitive development.<sup>87</sup> AI generates data based on what it has been asked to create and produces a type of “cultural evolution.”<sup>88</sup> As David Marx<sup>89</sup> puts it, “trends arise from cultural imitation”—imitation is not a static but a dynamic process that contributes to cultural transmission and evolution. In social contexts, humans imitate behaviors, which then evolve as they are passed from one generation to another.<sup>90,91</sup> Similarly, AI art is based on learning from human art that has evolved over a period of time, and, in this sense, AI art perpetuates artistic traditions. Much like human artists who iterate and re-interpret cultural norms to push boundaries, AI art can also contribute to the evolution of these traditions. Indeed, humans tend to appreciate art that draws upon and reimagines past traditions. AI can, in a way, pass down or perpetuate styles and conventions through its output, allowing new generations (both human and AI) to interact with and re-interpret past artistic forms. Just as cultural evolution in humans involves a blend of tradition and innovation, AI art might evolve by “imitating” past human creations while introducing new, unanticipated elements. These innovations might eventually influence human art, closing the loop between AI-generated culture and human cultural transmission.

Social Behaviour



Less

More

## Imitation of Others' Behaviour

**Figure 2. Shows a comparative evaluation of imitation across social behavior**

The panel illustrates examples of imitation or mimicry in social settings, ranging from what might be less, suggestive of socially unresponsive behavior (image A) to more, as awkward, literal social mirroring (image D), with illustrations of what might be more optimal or appropriate levels of imitation shown in images (B) and (C). The continuous line along the bottom represents the spectrum of imitation, ranging from less imitation on the left to more imitation on the right.  
Note. (A–C): images reproduced under the Pexels Free-Use License. Source: Pexels (cottonbro studio); D: image reproduced under a standard royalty-free license from iStock/Getty Images (Asset ID: 57421583, Image Source/iStock/Getty Images).

## CHARTING THE PATH FORWARD

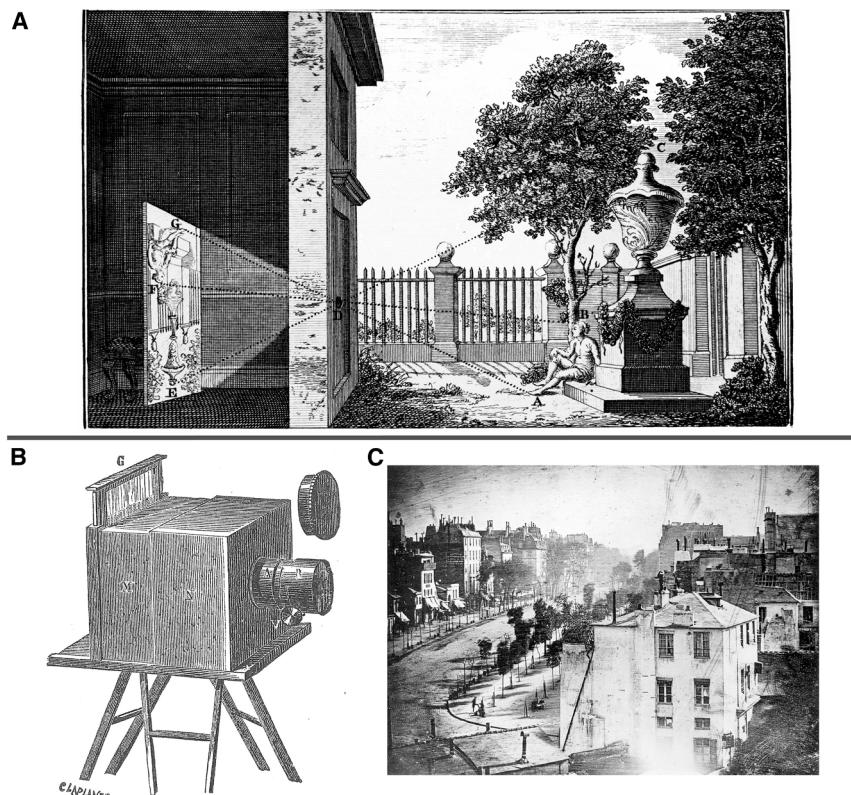
### Embracing AI as a collaborator rather than casting as an enemy—Historical and contemporary perspectives

Across different domains, whether in the arts or social behavior, human learning, development, and performance are deeply rooted in imitation. This fundamental ability to imitate not only has been essential to human social evolution but also plays a critical role in shaping how we create and interact with tools and technologies. Some of the tools used in artistic practices, as briefly discussed in the following, have been designed to further enable artists to achieve the “optimal” level of imitation of the world without compromising their artistic talent and creative originality. That said, AI tools are not only present in the arts today but are likely to stay and play an increasingly important role in the future. Therefore, it is essential to shift the focus from conflict and opposition to the potential benefits of collaboration between AI tools and human creativity. Historically, new technologies in art have often been met with skepticism and resistance; however, many of these once distrusted innovations have eventually become essential to artistic progress and have markedly advanced and enriched the arts.

Since rendering reality with fidelity has historically been a central tenet of art, Leonardo da Vinci in the 16th century is credited with providing the first detailed written description of the **camera obscura**, a device that allowed artists to capture nature with remarkable precision, almost to the point of illusion<sup>47</sup> (Figure 3). Among the most famous users of the camera obscura was the Dutch artist, Johannes Vermeer. Art historians, such as Hockney<sup>92</sup> and Steadman,<sup>93</sup> have argued that many of Vermeer’s masterpieces were created with the assistance of this tool. Despite some controversy over its aesthetic implications—with critics such as Kemp<sup>94</sup> deeming its use as similar

to “cheating”—the prevailing view among the art historians is more conciliatory. Gussow<sup>95</sup> has argued that the use of camera obscura should be regarded as a legitimate artistic tool rather than a substitute that undermines artistic talent. Supporting this view, a research study by Hantula et al.<sup>96</sup> has found that knowledge of Vermeer’s use of the camera obscura did not diminish his art appreciation but contributed to an enhanced awareness of his creative process. This suggests that the use of camera obscura in the visual arts aligns with the long-standing tradition, where artists aimed to closely reproduce nature. By including the camera obscura into their practice, artists were able to effectively bridge the gap between more and less imitation. This also highlights that the integration of technology in creative processes should be regarded as an evolution of artistic methods rather than a compromise of authenticity.

**Photography** represents another successful integration of technology into the arts, starting in the 19th century. From its invention, photography captivated artists by providing a means to capture details beyond the capability of the human eye, profoundly impacting the trajectory of artistic styles.<sup>97,98</sup> Initially regarded as an educational tool, photography provided unparalleled accuracy in portraiture, especially for commissioned portrait works. Artists such as Delacroix, Courbet, Cézanne, Toulouse-Lautrec, and Munch have used photography to create portraits of historical figures.<sup>99</sup> Furthermore, photography inspired new and more daring composition styles, characterized by contorted poses, radical cropping, and unconventional perspectives, as seen in the works of artists such as Mary Cassatt, Degas, and Caillebotte. It has also served as a valuable resource and inspiration for painters of exotic subject matters, such as Henri Rousseau and Paul Gauguin.<sup>97–99</sup> Today, photography has evolved into a respected art form in its own right, demonstrating the enduring impact of technological innovation on artistic expression. Furthermore, the example of photography



**Figure 3.** Shows early examples of optical and photographic technologies used to enhance imitation in visual art

(A) Presents an example of James Ayscough's 1750 illustration of a Camera Obscura Room.

(B) Shows the first known photography camera, the Daguerreotype, by Louis Daguerre in 1838.

(C) Illustrates one of the earliest photographs, *Boulevard du Temple, Paris*, by Louis Daguerre in 1838.

Note. (A): image reproduced under the Creative Commons Attribution 4.0 license. Source: Wellcome Library/Wikimedia Commons; (B and C): images reproduced from the public domain. Source: Wikimedia Commons.

strengthens the idea that artistic tools serve as instruments that enable artists to achieve their goal of imitating the observable world while maintaining both authenticity and creative originality. Through the use of tools such as photography, artists aimed to achieve the right balance in imitation—capturing sufficient elements of the real world to convey its essence, yet not too much as to compromise their original artistic individuality.

One example of AI being used as a collaborative tool in the arts is the work of Mario Klingemann, who is considered a pioneer in the application of neural networks within artistic practice. Klingemann's art explores broad themes of creativity, culture, and perception through the lens of machine learning and AI. His work has been successfully exhibited at prominent venues, such as the Ars Electronica Festival, the Metropolitan Museum of Modern Art in New York, the Photographers' Gallery in London, and the Center Pompidou in Paris. Klingemann's work highlights the potential of AI in expanding the scope of human creativity.<sup>100</sup> In a similar vein, Steve DiPaola's work algorithmically simulates brushstrokes, composition, and lighting effects, drawing on theories of human creativity and further illustrating how AI can serve as a collaborative tool in artistic practice.<sup>101</sup> Taken together, these ideas suggest that technological tools such as the camera obscura and photography have consistently played an important role in the arts, not by diminishing artistic talent but by expanding the possibilities for creative expression. The broader implication is that the integration of technology into artistic practices should be seen as an evolution of artistic practices. However, especially regarding the AI art tools, as these become more sophisticated, it is also

essential that they are used responsibly. Artists and creators should ensure that their use of technology respects the standards of authenticity, fairness, and transparency in their work, balancing innovation with ethical considerations.

## FUTURE DIRECTIONS

As AI technologies become increasingly integrated into society, facilitating access to education and knowledge dissemination for artists, students, researchers, and the general public will be essential for future development. Specifically, AI-generated art presents a unique opportunity for interdisciplinary collaboration between artists and scientists. Such partnerships could explore biases toward AI-generated art and address the ethical challenges related to authorship, ownership, and cultural appropriation. Building on some existing research, and addressing clear gaps, in the following, we highlight several key research questions to advance understanding at the intersection of psychology, cognitive neuroscience, and the evolving role of AI in art and education.

- (1) To what extent does the negative bias against AI technologies impact individuals' judgments regarding the legitimacy and fairness of AI-generated art,<sup>24</sup> especially concerning intellectual property rights, creative ownership,<sup>102</sup> and the potential for exploitation or misuse of human cultural heritage?
- (2) To what extent do factors such as mere exposure, familiarity, knowledge of AI systems, and previous expertise with traditional art shape aesthetic preferences for AI-generated versus human-made art?
- (3) What are the neural correlates of emotional responses to AI-generated art in comparison to traditional art, and how do these responses vary across different professions, age groups, and cultural backgrounds?

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## Glossary

**AI-generated art** refers to artistic outputs produced using generative AI technologies that learn from large datasets to create new visual content. This definition encompasses a spectrum of creative processes, from autonomous generation (where AI produces outputs with minimal human intervention) to collaborative approaches involving significant human input through prompt engineering, parameter setting, and output refinement. While recognizing the potential for more granular categorizations, this paper uses the term broadly to include any artwork that involves AI tools at any stage of the creative process. We also note that in practice most creative outputs are likely to sit along a continuum of human-AI co-creation, from those shaped almost entirely by human intervention (e.g., selective curation, manual processing, and post-generation editing) to those generated with minimal human mediation (e.g., providing a short prompt and pressing go). Furthermore, these processes may also differ in terms of interaction design, following the Co-Creative Framework for Interaction<sup>103</sup> or possibly the Co-Creative Design Framework.<sup>104</sup> While such variations may influence both the creative outcomes and their reception,<sup>105,106</sup> a deeper exploration of human-AI co-creation lies beyond the scope of the present paper.

**Generative AI** is a subtype of AI technology focused on generating new content by learning patterns from existing data. Unlike traditional AI, which primarily analyzes and interprets existing data, generative AI synthesizes new outputs, such as text, images, and synthetic data by modeling the patterns it has learned from prior data. This technology operates through models, such as generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models, which learn underlying patterns within data and generate new instances that closely resemble real-world (i.e., non-artistically generated) examples. Note that, in this paper, we do not draw distinctions between AI-generated art (and research about it) from pre-GANs/pre-Gen AI vs. artwork being made today with these more advanced methods. We raise the distinctions of these different approaches on the way AI-generated art is made and appreciated as an area for further research.

**Deep Dream** is an AI technology developed by Google that uses convolutional neural networks (CNNs) to modify existing images into surreal, dream-like visuals. Rather than generating new images from scratch, it transforms an image into a stylized, surreal version by amplifying the features the CNN has learned to recognize during training.

**Echolalia** is the involuntary repetition of words or sounds, while echopraxia refers to the imitation of another person's actions or movements.

**Large language models** (LLMs) are a type of AI system trained on vast textual datasets to process and generate human-like language. These AI models use deep learning techniques to analyze, recognize, and predict linguistic patterns, supporting tasks such as translation, text generation, and human-like conversation. Examples of LLMs include GPT-4 (OpenAI) and LLaMA (Meta). While LLMs can describe images or generate text prompts for art tools, they do not directly produce images. That is completed by distinct text-to-image models, which produce the visual outputs by modeling semantic nuances, artistic styles, and creative prompts.

**MidJourney** is a text-to-image tool based on diffusion model architectures that generates images from text descriptors.

**Over-imitation** is the tendency to imitate not only the relevant behaviors but also behaviors that are irrelevant or have no functional purpose.

**Mimicry and chameleon effects** refer to the nonconscious tendency to mimic another person's postures, mannerisms, and facial expressions during social interactions.

**Ostracism** is the intentional exclusion or rejection of an individual or group from a social context or interaction.

**Camera obscura** is a device made from convex lenses that project an image onto a screen, allowing an artist to trace the outline of an object or scene, rather than draw it from scratch. Using the camera obscura while creating a painting can result in an almost photographic image, although the end result would be a painting on canvas.

**Photography** (in its literal sense meaning "writing with light") was invented in 1839 in Paris by the artist and inventor Louis-Jacques-Mandé Daguerre as a means of capturing images in two-dimensional form through the use of light-sensitive materials.

## AUTHOR CONTRIBUTIONS

I.B.: initial conceptualization, conceptual development, literature review, visualization, writing – original draft, and writing – review and editing; K.M.D.: conceptual development and writing – review and editing; R.R.: conceptual development, literature review, and writing – review and editing; E.S.C.: conceptual development, literature review, visualization, writing – review and editing, supervision, and funding acquisition.

## DECLARATION OF INTERESTS

The authors declare no competing interests.

## REFERENCES

1. Drimmer, S. (2021). How AI is hijacking art history (The Conversation).
2. Hitti, N. (2018). Christie's sells AI-created artwork painted using algorithm for \$432,000 (De Zeen).
3. Goetze, T.S. (2024). AI art is theft: Labour, extraction, and exploitation: Or, on the dangers of stochastic Pollocks. In Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency, pp. 186–196. <https://doi.org/10.1145/3630106.3658898>.
4. Mazzone, M., and Elgammal, A. (2019). Art, Creativity, and the Potential of Artificial Intelligence. *Arts* 8, 26. <https://doi.org/10.3390/arts8010026>.
5. Cohn, G. (2018). AI Art at Christie's Sells for \$432,500, 25 (The New York Times), p. 551.
6. Goldberg, B. (2018). First-ever auction of AI-created artwork set for Christie's gavel (Reuters).
7. France-Presse (2018). Portrait Made Entirely Using AI Algorithm Sells For More Than \$400,000 (NTDV).
8. Jiang, H.H., Brown, L., Cheng, J., Khan, M., Gupta, A., Workman, D., and Gebru, T. (2023). AI Art and its Impact on Artists. In Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society (Association for Computing Machinery), pp. 363–374. <https://doi.org/10.1145/3600211.3604681>.
9. Tyka, M.. Portraits of Imaginary People/Interalia Magazine. <https://www.interaliasmag.org/audiovisual/mike-tyka/>.
10. Roose, K. (2022). An A.I.-Generated Picture Won an Art Prize. Artists Aren't Happy (The New York Times).
11. Mathur, A. (2024). Artificial Intelligence versus/ Human Artists: AI as a Creative Collaborator (CenterforArtLaw).
12. Chamberlain, R., Mullin, C., Scheerlinck, B., and Wagemans, J. (2018). Putting the Art in Artificial: Aesthetic Responses to Computer-Generated Art. *Psychol. Aesthet. Creativity Arts* 12, 177. <https://doi.org/10.1037/aca0000136.supp>.

13. Darda, K., Carre, M., and Cross, E. (2023). Value attributed to text-based archives generated by artificial intelligence. *R. Soc. Open Sci.* 10, 220915. <https://doi.org/10.1098/rsos.220915>.
14. Darda, K.M., and Cross, E.S. (2023). The computer, A choreographer? Aesthetic responses to randomly-generated dance choreography by a computer. *Helicon* 9, e12750. <https://doi.org/10.1016/j.heliyon.2022.e12750>.
15. Gangadharbatla, H. (2021). The Role of AI Attribution Knowledge in the Evaluation of Artwork. *Empir. Stud. Arts* 40, 125–142. <https://doi.org/10.1177/0276237421994697>.
16. Ha, A.Y.J., Passananti, J., Bhaskar, R., Shan, S., Southen, R., Zheng, H., and Zhao, B.Y. (2024). Organic or diffused: Can we distinguish human art from ai-generated images? In Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security (Association for Computing Machinery), pp. 4822–4836. <https://doi.org/10.1145/3658644.3670306>.
17. Samo, A., and Highhouse, S. (2025). Artificial Intelligence and Art: Identifying the Aesthetic Judgment Factors That Distinguish Human and Machine-Generated Artwork. *Psychol. Aesthet. Creativity Arts* 19, 1084–1098. <https://doi.org/10.1037/aca0000570>.
18. Agudo, U., Arrese, M., Liberal, K.G., and Matute, H. (2022). Assessing Emotion and Sensitivity of AI Artwork. *Front. Psychol.* 13, 879088. <https://doi.org/10.3389/fpsyg.2022.879088>.
19. Hong, J.W., Peng, Q., and Williams, D. (2021). Are you ready for artificial Mozart and Skrillex? An experiment testing expectancy violation theory and AI music. *New Media Soc.* 23, 1920–1935. <https://doi.org/10.1177/1461444820925798>.
20. Di Dio, C., Ardizzi, M., Schieppati, S.V., Massaro, D., Gilli, G., Gallese, V., and Marchetti, A. (2025). Art made by artificial intelligence: The effect of authorship on aesthetic judgments. *Psychol. Aesthet. Creativity Arts* 19, 1164–1176. <https://doi.org/10.1037/aca0000602>.
21. Hong, J.W., and Curran, N.M. (2019). Artificial intelligence, artists, and art: Attitudes toward artwork produced by humans vs. artificial intelligence. *ACM Transactions on Multimedia Computing. Commun. Appl.* 15, 1–16. <https://doi.org/10.1145/3326337>.
22. Moffat, D., and Kelly, M. (2006). An investigation into people's bias against computational creativity in music composition. *Assessment* 13, 1–8.
23. Ragot, M., Martin, N., and Cojean, S. (2020). AI-generated vs. human artworks: a perception bias towards artificial intelligence? In Conference on Human Factors in Computing Systems - Proceedings (Association for Computing Machinery), pp. 1–10. <https://doi.org/10.1145/3334480.3382892>.
24. Bara, I., Ramsey, R., and Cross, E.S. (2025). AI contextual information shapes moral and aesthetic judgments of AI-generated visual art. *Cognition* 257, 106063. <https://doi.org/10.1016/j.cognition.2025.106063>.
25. Carroll, N. (1999). *Philosophy of Art: A Contemporary Introduction* (Routledge).
26. Chatterjee, A. (2022). Art in an age of artificial intelligence. *Front. Psychol.* 13, 1024449. <https://doi.org/10.3389/fpsyg.2022.1024449>.
27. Danto, A.C. (1981). *The Transfiguration of the Commonplace* (Harvard University Press).
28. Davies, S. (2012). *The Artful Species: Aesthetics, Art, and Evolution* (Oxford Academic).
29. Dissanayake, E. (1995). *Homo Aestheticus : Where Art Comes from and Why* (University of Washington Press).
30. Gaut, B., and McIver Lopes, D. (2001). *The Routledge Companion to Aesthetics* (Routledge).
31. Shao, Y., Zhang, C., Zhou, J., Gu, T., and Yuan, Y. (2019). How does culture shape creativity? A mini-review. *Front. Psychol.* 10, 1219. <https://doi.org/10.3389/fpsyg.2019.01219>.
32. Young, O.J. (2001). *Art and Knowledge* (Routledge).
33. Becker, H.S. (1982). *Art Worlds* (University of California Press).
34. Hyde, L. (1983). *The Gift* (Vintage Books).
35. Cha, Y.J., Baek, S., Ahn, G., Lee, H., Lee, B., Shin, J.e., and Jang, D. (2020). Compensating for the loss of human distinctiveness: The use of social creativity under Human–Machine comparisons. *Comput. Hum. Behav.* 103, 80–90. <https://doi.org/10.1016/j.chb.2019.08.027>.
36. Tubadji, A., Huang, H., and Webber, D.J. (2021). Cultural proximity bias in AI-acceptability: The importance of being human. *Technol. Forecast. Soc. Change* 173, 121100. <https://doi.org/10.1016/j.techfore.2021.121100>.
37. Perdreau, F., and Cavanagh, P. (2013). The artist's advantage: Better integration of object information across eye movements. *Perception* 4, 380–395. <https://doi.org/10.1088/0309-0460/42/3/380>.
38. Seeley, W., and Kozbelt, A. (2008). Art, Artists, and Perception: A Model for Premotor Contributions to Perceptual Analysis and Form Recognition. *Philos. Psychol.* 21, 149–171. <https://doi.org/10.1080/09515080801976573>.
39. Gunkel, D.J. (2017). Rethinking Art and Aesthetics in the Age of Creative Machines: Editor's Introduction. *Philos. Technol.* 30, 263–265. <https://doi.org/10.1007/s13347-017-0281-3>.
40. Millet, K., Buehler, F., Du, G., and Kokkoris, M.D. (2023). Defending humankind: Anthropocentric bias in the appreciation of AI art. *Comput. Hum. Behav.* 143, 107707. <https://doi.org/10.1016/j.chb.2023.107707>.
41. Sawyer, R.K. (2012). *The Science of Human Innovation: Explaining Creativity* (Oxford University Press).
42. Schmitt, B. (2020). Speciesism: an obstacle to AI and robot adoption. *Mark. Lett.* 31, 3–6. <https://doi.org/10.1007/s11002-019-09499-3>.
43. Dewey, J. (1934). *Art as Experience* (Minton Balch & Company).
44. Climenhaga, R. (2008). *Pina Bausch*, 1st ed. (Routledge).
45. Lu, L.F.L. (2005). Pre-service art teacher negative attitudes and perceptions of computer-generated art imagery: Recommendations for pre-service art education programs. *Vis. Arts Res.* 31, 89–102.
46. Aristotle (1996). *Poetics* (M. Heath, Trans.) (Penguin Classics). (Original work published 4th century BCE).
47. Blinder, D. (1986). In defense of pictorial mimesis. *J. Aesthet. Art Critic.* 45, 19–27.
48. Halliwell, S. (2002). *The Aesthetics of Mimesis: Ancient Texts and Modern Problems* (Princeton University Press).
49. Huhn, T. (2004). *Imitation and Society: The Persistence of Mimesis in the Aesthetics of Burke, Hogarth, and Kant* (Penn State University Press).
50. Boschloo, A.W.A., Coutré, J.N., Dickey, S.C., and Sluijter-Seijffert, N.C. (2011). *Aemulatio - Imitation, Emulation and Invention in Netherlandish Art from 1500 to 1800* (Waanders).
51. Liu, Y., and Carter, C.L. (2014). *Aesthetics of Everyday Life: East and West* (Cambridge Scholars Publishing).
52. Mattick, P. (2003). *Art in its Time: Theories and Practices of Modern Aesthetics* (Routledge).
53. Fried, M. (1992). *Courbet's Realism* (University of Chicago Press).
54. Ormiston, R. (2011). *The Life and Works of Leonardo Da Vinci: A Full Exploration of the Artist, His Life and Context, with 500 Images and a Gallery of His Greatest Works* (Hermes House).
55. Shiff, R. (1984). *Cézanne and the End of Impressionism: A Study of the Theory, Technique, and Critical Evaluation of Modern Art* (University of Chicago Press).
56. Elderfield, J. (1976). The “wild Beasts”: Fauvism and Its Affinities (Museum of Modern Art).
57. Cooper, D., and Tinterow, G. (1983). *The Essential Cubism, 1907-1920: Braque, Picasso & Their Friends* (Tate Gallery).
58. Ganterfuerer-Trier, A. (2004). *Cubism* (Taschen).
59. Millard, C.W. (1976). *Fauvism*. *Hudson Rev.* 29, 576–580.
60. Ferrulli, H., May, J., and Sims, P. (2014). *Richard Estes' Realism* (Portland Museum of Art).
61. Taylor, J.R. (2009). *Exactitude: Hyperrealist Art Today* (Thames & Hudson).

62. Legare, C.H., and Nielsen, M. (2015). Imitation and Innovation: The Dual Engines of Cultural Learning. *Trends Cogn. Sci.* 19, 688–699. <https://doi.org/10.1016/j.tics.2015.08.005>.
63. Brass, M., and Heyes, C. (2005). Imitation: Is cognitive neuroscience solving the correspondence problem? *Trends Cogn. Sci.* 9, 489–495. <https://doi.org/10.1016/j.tics.2005.08.007>.
64. Clay, Z., Over, H., and Tennie, C. (2018). What drives young children to over-imitate? Investigating the effects of age, context, action type, and transitivity. *J. Exp. Child Psychol.* 166, 520–534. <https://doi.org/10.1016/j.jecp.2017.09.008>.
65. Heyes, C. (2011). Automatic imitation. *Psychol. Bull.* 137, 463–483. <https://doi.org/10.1037/a0022288>.
66. Meltzoff, A.N., and Prinz, W. (2002). *The Imitative Mind: Development, Evolution and Brain Bases* (Cambridge University Press).
67. Hamilton, A.F.d.C. (2015). The neurocognitive mechanisms of imitation. *Curr. Opin. Behav. Sci.* 3, 63–67. <https://doi.org/10.1016/j.cobeha.2015.01.011>.
68. Chartrand, T.L., and van Baaren, R. (2009). Chapter 5 Human Mimicry. In *Advances in Experimental Social Psychology*, P.Z. Mark, ed. (Academic Press), pp. 219–274. [https://doi.org/10.1016/s0065-2601\(08\)00405-x](https://doi.org/10.1016/s0065-2601(08)00405-x).
69. Kavanagh, L.C., and Winkielman, P. (2016). The Functionality of Spontaneous Mimicry and Its Influences on Affiliation: An Implicit Socialization Account. *Front. Psychol.* 7, 458. <https://www.frontiersin.org/articles/10.3389/fpsyg.2016.00458>.
70. Wang, Y., and Hamilton, A.F.d.C. (2012). Social Top-down Response Modulation (STORM): A model of the control of mimicry in social interaction. *Front. Hum. Neurosci.* 6, 153. <https://doi.org/10.3389/fnhum.2012.00153>.
71. Chartrand, T.L., and Lakin, J.L. (2013). The Antecedents and Consequences of Human Behavioral Mimicry. *Annu. Rev. Psychol.* 64, 285–308. <https://doi.org/10.1146/annurev-psych-113011-14375430>.
72. Lakin, J.L., Jefferis, V.E., Cheng, C.M., and Chartrand, T.L. (2003). The Chameleon Effect as Social Glue: Evidence for The Evolutionary Significance of Nonconscious Mimicry. *J. Nonverbal Behav.* 27, 145–162.
73. Lyons, D.E., Young, A.G., and Keil, F.C. (2007). The hidden structure of overimitation. *Proc. Natl. Acad. Sci. USA* 104, 19751–19756.
74. Over, H., and Carpenter, M. (2013). The Social Side of Imitation. *Child Dev. Perspect.* 7, 6–11. <https://doi.org/10.1111/cdep.12006>.
75. Kinzler, K.D., Corriveau, K.H., and Harris, P.L. (2011). Children's selective trust in native-accented speakers. *Dev. Sci.* 14, 106–111.
76. Whiten, A., Allan, G., Devlin, S., Kseib, N., Raw, N., and McGuigan, N. (2016). Social learning in the real-world: "Over-imitation" occurs in both children and adults unaware of participation in an experiment and independently of social interaction. *PLoS One* 11, e0159920. <https://doi.org/10.1371/journal.pone.0159920>.
77. Over, H., and Carpenter, M. (2009). Priming third-party ostracism increases affiliative imitation in children. *Dev. Sci.* 12, F1–F8.
78. Spoor, J.R., and Williams, K. (2007). the evolution of an ostracism detection system. In *The evolution of the social mind: Evolutionary psychology and social cognition*, J.P. Forgas, M. Haselton, and W. Von Hippel, eds. (Psychology Press), pp. 279–292.
79. Decety, J., and Meltzoff, A.N. (2011). Empathy, Imitation, and the Social Brain. In *Empathy: Philosophical and Psychological Perspectives* (Oxford University Press), pp. 58–81.
80. Watanabe, R., Kim, Y., Kuruma, H., and Takahashi, H. (2022). Imitation encourages empathic capacity toward other individuals with physical disabilities. *Neuroimage* 264, 119710.
81. Aldridge, M.A., Stone, K.R., Sweeney, M.H., and Bower, T.G.R. (2000). Preverbal children with autism understand the intentions of others. *Dev. Sci.* 3, 294–301.
82. Rogers, S.J., Hepburn, S.L., Stackhouse, T., and Wehner, E. (2003). Imitation performance in toddlers with autism and those with other developmental disorders. *J. Child Psychol. Psyc.* 44, 763–781.
83. Vivanti, G., Nadig, A., Ozonoff, S., and Rogers, S.J. (2008). What do children with autism attend to during imitation tasks? *J. Exp. Child Psychol.* 101, 186–205.
84. Williams, J.H., Whiten, A., Suddendorf, T., and Perrett, D.I. (2001). Imitation, mirror neurons and autism. *Neurosci. Biobehav. Rev.* 25, 287–295.
85. Conway, C.C., Forbes, M.K., Forbush, K.T., Fried, E.I., Hallquist, M.N., Kotov, R., Mullins-Sweatt, S.N., Shackman, A.J., Skodol, A.E., South, S.C., et al. (2019). A Hierarchical Taxonomy of Psychopathology Can Transform Mental Health Research. *Perspect. Psychol. Sci.* 14, 419–436. <https://doi.org/10.1177/1745691618810696>.
86. Fried, E.I. (2022). Studying Mental Health Problems as Systems, Not Syndromes. *Curr. Dir. Psychol. Sci.* 31, 500–508. <https://doi.org/10.1177/09637214221114089>.
87. Corrêa, G.P. (2023). On Creativity and Generative-AI Aesthetics: some thoughts and concerns. *Semeiosis* 11, 32–50.
88. Duéñez-Guzmán, E.A., Sadedin, S., Wang, J.X., McKee, K.R., and Leibo, J.Z. (2023). A social path to human-like artificial intelligence. *Nat. Mach. Intell.* 5, 1181–1188.
89. Cacal, N. (2024). AI, Status and Culture (Medium).
90. Heyes, C. (2009). Evolution, development and intentional control of imitation. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 364, 2293–2298.
91. Farmer, H., Ciaunica, A., and Hamilton, A.F.D.C. (2018). The functions of imitative behaviour in humans. *Mind Lang.* 33, 378–396.
92. Hockney, D. (2001). *Secret Knowledge: Rediscovering the Techniques of the Old Masters* (Penguin Putnam).
93. Steadman, P. (2001). *Vermeer's Camera: Uncovering the Truth behind the Masterpieces* (Oxford University Press).
94. Kemp, M. (1990). *The Science of Art: Optical Themes in Western Art from Brunelleschi to Seurat* (Yale University Press).
95. Gussow, M. (2001). *Old Masters Pursued by Artistic Gumshoes* (New York Times).
96. Hantula, D.A., Sudduth, M.M., and Clabaugh, A. (2009). Technological Effects on Aesthetic Evaluation: Vermeer and the Camera Obscura. *Psychol. Rec.* 59, 323–333. <http://www.vermeerscamera.co.uk>.
97. Davenport, A. (1999). *The History of Photography: An Overview* (University of New Mexico Press).
98. Sweet, D. (2021). Before and after photography. *J. Contemp. Paint.* 7, 163–175.
99. McCouat, P. (2023). Early influences of photography on art – Part 1: Initial impacts. *J. Art Soc.* <https://www.artinsociety.com/pt-1-initial-impacts.html>
100. Klingemann, M.. AI Artists. <https://www.katevsgalerie.com/mario-klingemann>.
101. DiPaola, S. (2009). Exploring a parameterised portrait painting space. *Int. J. Arts Technol.* 2, 82–93.
102. Epstein, Z., Levine, S., Rand, D.G., and Rahwan, I. (2020). Who gets credit for AI-generated art? *iScience* 23, 101515. <https://doi.org/10.1016/j.isci.2020.101515>.
103. Rezwana, J., and Maher, M.L. (2023). Designing creative AI partners with COFI: A framework for modeling interaction in human-AI co-creative systems. *ACM Trans. Comput. Hum. Interact.* 30, 1–28.
104. Davis, N., Sherson, J., and Rafner, J. (2025). The Co-Creative Design Framework for Hybrid Intelligence. In *Proceedings of the 2025 Conference on Creativity and Cognition*, S. Andolina, N. Bryan-Kinns, and S. F. Alaoui, eds. (Association for Computing Machinery), pp. 560–572.
105. Rafner, J., Beaty, R.E., Kaufman, J.C., Lubart, T., and Sherson, J. (2023). Creativity in the age of generative AI. *Nat. Hum. Behav.* 7, 1836–1838.
106. Oppenlaender, J. (2022). The creativity of text-to-image generation. In *Proceedings of the 25th international academic mindtrek conference (Association for Computing Machinery)*, pp. 192–202. <https://doi.org/10.1145/3569219.3569352>.